Hybrid Deep Learning Approach for Enhancing Brain Tumor Detection in MRI Scans

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Contents

Abstract 1

1.0 Introduction 2

1.1 The Problem 3

1.2 Research Gap 3

1.2.1 Research goals and questions 4

1.3 The study's objectives and inquiries 4

1.4. Objectives of the Study 5

1.5 A brief thought 5

1.5.1 Scope of the Study 6

1.5.2. Examining Various MRI Modes 7

1.5.3. Artificial intelligence that can be described and collaborate with physicians 7

1.5.4. A strategy that is flexible and easy to utilize 7

1.5.5 The investigation will encompass more than merely technical details 7

1.6 Literature Review 8

1.7 Research Methodology 14

1.8 References 15

Hybrid Deep Learning Approach for Enhancing Brain Tumor Detection in MRI Scans

Abstract

One of the most serious neurological problems is brain tumors. Finding them early and correctly is critical so that they may be treated and patients have improved results. MRI is the best non-invasive imaging method since it can show small details in soft tissues and has numerous sequences that work well together (T1, T2, FLAIR, T1ce). There can be differences in MRI scans, tumors can look different, and the tumor and the tissues around it don't look very different. This makes it challenging to find tumors with any accuracy. conventional machine learning techniques that rely on manually produced features often lack stability and flexibility, rendering them less effective in clinical environments.

Deep learning techniques, especially convex neural networks (CNNs), helped with tumor detection by self- learning features from images. But CNNs typically only pick up on local qualities, and they don't always get how different sections of the brain are connected around the world. Hybrid deep learning systems that combine CNNs with attention modules, transformers, or graph-based algorithms make things more accurate, but they are hard for researchers who only know basic Python to utilize in real time because they are very complicated to program. This paper proposes a straightforward hybrid algorithmic methodology that employs CNN-based feature extraction and attention processes to detect brain tumors in multi-modal MRI data and delineate them into distinct components. The technique is designed to effectively utilize complimentary information from the T1, T2, FLAIR, and T1ce sequences while remaining accessible to anyone with fundamental Python proficiency. Doctors might be able to make clear and easy-to-understand guesses with simple AI tools like Grad-CAM and attention heat maps. The suggested method tries to find the best balance between speed, accuracy, and convenience of usage. This dataset is well-known and is called BraTS 2020–2023. We will use it to test how well Dice performs with accuracy, specificity, and precision. The system should be able to work with different types of MRI scans and in places where there aren't many good tools. This will help you connect what you study in school to what you do in real life. The main goal of this project is to create a brain tumor detection system that works well, is simple to use, and can be used in real life. AI will help doctors make better medical shots and find problems more quickly.

1.0 Introduction

Brain tumors are one of the most deadly neurological conditions that can kill you. They also have a huge effect on how well you live. Early detection and a correct diagnosis are crucial for therapy to function. A lot of people get MRIs to look for brain tumors because they don't have to go through radiation and the photos are very clear. There are other types of MRI scans, like T1, T2, FLAIR, and contrast-enhanced T1 (T1ce) that together reveal a lot of information about a tumor's size, shape, and location.

Finding cancer is still hard, even though MRI has its pros. Tumors come in varying sizes, shapes, and brightness levels, and they normally blend in with the tissue around them. It takes time for doctors to look at photos by hand, and they don't always get it right. This makes it more probable that the inaccurate diagnosis may be made, especially in hospitals with a lot of people. There are automatic options that use machine learning, however traditional approaches rely on characteristics that are produced by hand and don't function well with a lot of different MRI datasets.

Deep learning techniques, especially convex neural networks (CNNs), have enhanced computers' ability to detect cancers by extracting information directly from images. CNNs, on the other hand, usually pick up on trends in one area and might not see patterns in other areas. Detection can be more accurate with more complex hybrid models that have attention, transforms, or graph-based modules. But these models are often challenging for researchers who simply know the basics of Python to utilize because they are hard to grasp and hard to compute. This study presents a straightforward algorithmic method for employing multi-modal MRI data to detect and distinguish brain tumors. The method employs both CNN-based feature extraction and attention approaches to find both local and global tumor features. Use explainable AI (XAI) methods like Grad-CAM and attention heatmaps to generate outputs that are easy for people to grasp. This helps doctors believe and make sense of the predictions. The approach should be useful, operate well on computers, and be easy for those with basic Python skills to use while still being quite precise. We will use standard datasets as BraTS 2020–2023 to test it using metrics such as accuracy, sensitivity, specificity, and the Dice coefficient. The suggested framework aims to convert brain tumor detection from scholarly research into tangible clinical implementation via a robust, transparent, and resource-efficient methodology.

1.1 The Problem

An MRI scan can't always tell the difference between brain tumors because they are so different from one another. Even for doctors with a lot of experience, it's hard to tell ones from another because they are all different in size, shape, intensity, and location. You might not be able to tell the difference between small and large brain tumors by hand because the bigger ones can change how regular brain structures work. It is also more likely that the wrong diagnosis will be made when the signs of both cancerous and normal tumors are present.
A lot of the time, manual reading is used for diagnosis, but it takes a long time and things can go wrong. Deep learning methods, such as CNNs, can find cancer on their own, but they only look at small details and don't always see the bigger picture. Advanced mixed models that use transformers or attention processes can solve this problem, but they are hard to compute and need a lot of data.

We need a useful and lightweight statistics system that can quickly find tumors using different types of MRI data (T1, T2, FLAIR, and T1ce) and give results that are easy to understand and put into practice. If there was such a system, researchers would not have to use as many complex models. Anyone with basic Python skills could use it and test it well.

1.2 Research Gap

AI and deep learning have come a long way in finding brain tumors, but there is still a lot of work to be done:

1. The models we have now are too intricate. Most hybrid models employ CNNs with transformers or graph-based networks, which makes them challenging for beginners to use and requires a lot of computing power.
2. Hard to get: A lot of deep learning algorithms make forecasts without saying how they got there, which makes it harder for doctors to believe them.
   Because they were trained on high-quality data sets like BraTS, existing models may not work as well with MRI scans that have low resolution or a lot of different types of data.
3. Integration of many modes: Combining different MRI sequences (T1, T2, FLAIR, T1ce) isn't always the ideal way to do things. We need better ways to use all the information from all the modalities in our calculations.

4. Motivation: This project aims to create a lightweight, algorithm-based framework for brain tumor detection that utilizes CNNs and attention mechanisms to capture both local and global tumor characteristics.

• Uses multi-modal MRI images well to help tell different kinds of cancer apart.
• Uses AI tools that can be taught to show items in pictures.

• It can be done on computers, and those who know a little bit of Python can use it, so more experts can use it. The ultimate goal is to find a way to connect complicated research models that work effectively with algorithms that can be used in the real world and evaluated on human data.

1.2.1 Research goals and questions

The goal of this project is to make it easier to quickly find brain cancer by using multi-modal MRI data. The system will use CNN-based feature extraction, focus steps, and basic artificial intelligence all at once to create results that are clear and helpful. The search will examine the ensuing inquiries:

- How can a simple algorithm quickly find brain tumors and tell them apart in MRI images that use different forms of data (T1, T2, FLAIR, T1ce)?
- How can a simple system be created that can find tumor signals on both a small and large scale by using attention processes?
- How can doctors understand what AI technologies like Grad-CAM and saliency maps can say?
- How does the suggested approach stack up against other deep learning models when evaluated on datasets like BraTS?

1.3 The study's objectives and inquiries

The goal of this project is to speed up the process of finding brain tumors by using multi-modal MRI scans. It will employ CNN-based feature discovery, focus phases, and rudimentary AI all at once to generate outputs that are helpful and give you information. We will look at the following things: There are several types of data that MRI imaging uses, include T1, T2, FLAIR, and T1ce. How can a program that is simple to use quickly discover brain lesions and tell them apart?
How can we use the attention process to develop a simple instrument that can discover cancer in both little and large amounts? AI tools like Grad-CAM and saliency charts can help doctors, but they need to know how to utilize them.
Right now, this method is being evaluated on datasets like BraTS. How does it relate to other deep learning models?

1.4. Objectives of the Study

The investigation has numerous purposes, including:

- To help locate brain lesions in multi-modal MRI data and deliver accurate descriptions, CNNs and focus tasks can be employed more effectively.
- Add AI techniques that doctors can understand to make the algorithm smarter so that the photos can be used.
- We will utilize the recommended technique in diverse imaging settings and keep track of the Dice score, accuracy, and performance to show that it works well on standard datasets (BraTS 2020–2023).

1.5 A brief thought

One of the most hazardous things that may happen is for the mind to grow. Magnetic resonance imaging (MRI) is the best way to find things without surgery because it may show many patterns, such as T1, T2, FLAIR, and T1ce (contrast-enhanced T1). It can also show more information in fragile tissues. However, tumors are not always easy to see because they can be different sizes, they don't stand out from other tissues, they make noise, and the quality of MRI scans can change.

Tumors have been found and classified using traditional machine learning methods that use hand-crafted features. These methods are easy to use and don't require much computer power, so researchers who aren't good at writing can use them. They might be put into action sometimes, but not all the time. This is especially true when they are used on MRI datasets that are either of low quality or of different sorts.

CNNs have made it easier to find cancer by teaching computers how to sort things in pictures. At times, CNNs can find patterns in small areas. They might not be able to show how different parts of the brain are connected to each other. This makes it harder to find lesions that aren't round or easy to see.

A new study looked at mixed techniques that use CNNs together with focus systems or optimized transformer modules to solve these issues. An attention-based strategy makes it easy to focus on the most relevant sections of MRI pictures. This approach works better to locate the

edges of tumors and put them together. Multi-modal MRI analysis uses MRI data from more than one scan to make the model better at spotting cancer. This is a simple approach to understand the information. To do this, use Grad-CAM and saliency maps, which are two machine learning technologies (XAI). Now, doctors are more likely to believe what the machine says. You don't need full-scale deep learning models to develop a real-time system that works in a clinical setting or one with few resources. You only need simple and quick ways. Even though things are getting better, several problems still exist: Most of the models that are already out there haven't been tested much with low-resolution or different types of MRI images because they were made for high-quality datasets. Doctors often can't give a full picture of a scenario because they can only use visual aids. It's hard to trade things in real time since big hybrid models need a lot of computer power. The goal of the study is to create a core algorithm-based system that can find brain cancer using CNN data extraction, attention processes, and XAI (clarifying artificial intelligence) methodologies. This approach uses multi-modal MRI images to make detection and division more efficient. You should be able to finish it with only a little bit of Python expertise, and everything should work as it should and be clear. This method fixes the problem of a study's quality not matching its worth. It makes sure that our opinion about brain cancer is strong and useful.

1.5.1 Scope of the Study

The procedure of identifying tumors and removing them the project's objective is to develop a mixed deep learning system capable of reliably identifying and categorizing brain cancer from MRI data. A method to accomplish this is to employ attention-based modules or transformers with intricate neural networks to extract localized information and document the brain's extensive social connections. We are interested in evaluating the method's efficacy on a variety of MRI data types, including T1, T2, FLAIR, and T1ce. This will enable us to more effectively identify small or unusually shaped tumors, identify the margins of tumors, and evaluate its performance on scans that are irregular and have low resolution. It may be hard to manage the situation due to shifts in the quality of the MRI, noise, and the various methods of image acquisition. It will prove advantageous.

1.5.2. Examining Various MRI Modes

In this endeavor, we will investigate the potential of combining various MRI patterns to more effectively describe and categorize cancers. The data from various image categories will be combined using robust fusion methods to extract valuable information. This will expedite the identification of specific tumor components, including the necrotic patches, the edema, and the nucleus that is expanding. The objective of this multi-modal study is to enhance the model's capacity to make precise diagnoses in clinical environments and to facilitate the differentiation between benign and malignant tumors.

1.5.3. Artificial intelligence that can be described and collaborate with physicians

To facilitate comprehension of the model's conclusions, the study will implement XAI tools such as Grad-CAM, saliency maps, and focus heatmaps. By doing so, physicians and radiologists can gain a more comprehensive understanding of the reasons why a specific region is classified as a tumor or not. This increases their likelihood of accepting AI-based analyses. The primary objective of the initiative is to ensure that these comprehension tools are operational in real-world scenarios. In this manner, the instruments can assist individuals in making decisions rather than merely displaying what they observe.

1.5.4. A strategy that is flexible and easy to utilize

The study will examine optimization techniques to develop a user-friendly and efficient pair model. The study will examine techniques such as transfer learning, model loss, and pruning. These can assist produce very accurate outcomes in clinical settings where resources are restricted. The model will undergo a series of tests to ensure that it is compatible with a variety of data, imaging events, and hospital settings. Diagnosis will necessitate less effort. The manner in which it alters the way in which physicians perform their duties

1.5.5 The investigation will encompass more than merely technical details

Additionally, a framework will be examined in terms of its potential to assist in the earlier detection of brain cancers, the establishment of interventions, and the monitoring of their

progression. The study's objective is to establish a connection between AI-based research models and healthcare in the real world by ensuring that the system implemented is both user-friendly and effective.

1.6 Literature Review

Recent advancements in deep learning have enabled computers to more accurately identify and differentiate between brain lesions in MRI images. Many individuals employ Convolutional Neural Networks (CNNs) due to their superior ability to extract hierarchical spatial features directly from imaging data, as opposed to other machine learning methods that necessitate the creation of features by hand [1][2]. U-Net and its variants, such as 3D U-Net, are highly effective in the separation of components of medical images. This is particularly true when it comes to aligning the margins of tumors in multi-modal MRI scans [3][4]. Conversely, CNNs are not always capable of identifying various types of cancer due to their inability to detect long-term connections and contextual information [5][6].

In order to circumvent these challenges, numerous individuals have proposed hybrid deep learning systems that incorporate CNNs with attention systems or models that are based on transformers. TransBTS and BiTr-Unet are two examples. Transformers and CNNs are employed to identify both local characteristics and the interconnections between entities worldwide. This results in a more accurate division [6][7]. In order to facilitate the identification of tumors, multi-path learning methods, such as multiPI-TransBTS, employ various MRI patterns (T1, T2, FLAIR, T1ce) [8]. A method that is fluid and simple to utilize the study will examine optimization techniques to develop a user-friendly and efficient mix model. The project will examine transfer learning, model reducing, and trimming as methods. These can assist provide very precise findings in clinical settings with limited resources. Hybrid methods, which combine ensemble methods, graph neural networks (GNNs), and CNNs, have also been employed to enhance the stability of models on a wider range of datasets [13][14]. Generative models, such as GANs, are increasingly employed to augment limited datasets. This renders tumor detection models more applicable in general [15][16].

Despite these advancements, the research that has been conducted thus far still contains deficiencies. Many studies evaluate models using high-quality datasets such as BraTS; however, there is a scarcity of research that evaluates their performance on real-world MRI scans that are low-resolution or contain a variety of data types [4][6][17]. Currently, explainability is primarily

restricted to visual results that are not applicable in clinical settings [10][18]. The utilization of hybrid models in real-time therapeutic environments is exceedingly challenging [12][19]. It is crucial to have a mixed deep learning system that can achieve the optimal equilibrium between speed, accuracy, and user-friendliness, particularly in clinical settings that are applied in real life. New research, such as [20]–[30], demonstrates that the integration of CNNs, transformers, and attention processes can enhance the quality of multi-modal MRI analysis. This establishes the foundation for the development of a hybrid framework that is both functional and beneficial in clinical settings. It is recommended that a variety of strategies be employed to develop a robust, logical, and effective model for recognizing and categorizing of brain malignancies in MRI scans. This will facilitate the connection between the models that are employed for research and those that are employed in practical applications.

S.No	Author & Year	Methodology	Dataset	Key Contribution	Research Gap	Ref. No.
1	O. Ronneberger et al., 2015	U-Net CNN	Medical Images	Semantic segmentation of biomedical images	Limited to local features, no global context	[1]
2	K. Simonyan & A. Zisserman, 2014	VGG CNN	ImageNet	Deep CNN architecture for feature extraction	Not optimized for MRI, lacks interpretability	[2]
3	K. He et al., 2016	ResNet	ImageNet	Residual learning to improve training of deep networks	Not applied to multi-modal MRI	[3]
4	B. H. Menze et al., 2014	BraTS Benchmark	BraTS 2015	Standardized brain tumor segmentation	Does not evaluate low-res MRI	[4]

				dataset		
5	F. Isensee et al., 2021	nnU-Net	BraTS 2020	Self-adapting U-Net framework	Heavy computational requirements	[5]
6	W. Wang et al., 2021	TransBTS	BraTS 2020	CNN + Transformer for segmentation	Complex, high GPU requirement	[6]
7	Q. Jia & H. Shu, 2021	BiTr-Unet	BraTS 2020	Combines CNN and transformer for MRI segmentation	Limited evaluation on heterogeneous MRI	[7]
8	H. Zhu et al., 2024	multiPI-TransBTS	BraTS 2020	Multi-path learning framework	High model complexity	[8]
9	J. Lin et al., 2023	CKD-TransBTS	BraTS 2020	Clinical knowledge-driven hybrid transformer	Limited real-world deployment	[9]
10	S. K. Mistry et al., 2023	Dynamic nnU-Net	BraTS 2020	Multi-scale feature enrichment	Not lightweight, slow inference	[10]
11	Z. Xiong et al., 2025	ResSAXU-Net	BraTS 2020	Efficient multimodal segmentation	Low explainability	[11]
12	A. Pourmahboubi	VGG19 + U-Net	BraTS 2020	Transfer learning for	Limited multi-modal fusion	[12]

	et al., 2025			small datasets		
13	J. Huang et al., 2025	CNN	BraTS 2020	Brain tumor detection with fewer MRI sequences	Limited accuracy	[13]
14	C. M. Umarani et al., 2024	Deep CNN	BraTS 2020	Review on segmentation improvements	No real-time evaluation	[14]
15	T. B. Nguyen-Tat et al., 2024	3D U-Net + Attention	BraTS 2020	Attention improves boundary delineation	Computationally heavy	[15]
16	L. Zhang et al., 2024	Lightweight CNN	BraTS 2020	Efficient segmentation for low-resource settings	Limited accuracy	[16]
17	A. Vossough et al., 2024	nnU-Net vs DeepMedic	Pediatric MRI	Benchmarking pediatric tumor segmentation	Dataset size limited	[17]
18	E. Zarenia et al., 2025	Multi-class CNN	BraTS 2020	Automated classification & segmentation	Explainability not included	[18]
19	R. Khan et al., 2025	Hybrid DL	BraTS 2020	Improved classification accuracy	Complexity limits deployment	[19]
20	M. M. Ahmed	ViT-GRU	BraTS	Combines ViT	Needs large dataset	[20]

	et al., 2024	hybrid	2020	and GRU for MRI analysis		
21	E. Gundogan, 2025	Explainable hybrid DL	BraTS 2020	XAI module integration	Only visual explanation, not clinical	[21]
22	A. Dehkordi et al., 2025	Lightweight CNN + Lévy optimizer	BraTS 2020	Optimized for efficiency	Limited clinical validation	[22]
23	S. Roy et al., 2025	Fibonacci-Net CNN	BraTS 2020	Lightweight automatic classification	Not multi-modal	[23]
24	A. Almuhaimeed et al., 2025	Swin Transformer + GAN	BraTS 2020	GAN augmentation improves dataset	Complex architecture	[24]
25	J. Zafar et al., 2025	Contrastive Latent GAN	BraTS 2020	Image synthesis + classification	Needs large GPU	[25]
26	R. Salakapuri et al., 2025	Hybrid DL + Ensemble	BraTS 2020	Improved detection robustness	Heavy computation	[26]
27	S. E. Nassar et al., 2024	MRI + Hybrid DL	BraTS 2020	Robust multi-class classification	Limited low-res MRI study	[27]
28	Y. Lyu et al., 2025	MWG-UNet++	BraTS 2020	Hybrid Transformer U-Net	Expensive inference	[28]

29	M. A. Ilani et al., 2025	U-Net + Transfer learning	BraTS 2020	Improved small dataset segmentation	Limited real-time analysis	[29]
30	D. Rastogi et al., 2025	DL + Survival prediction	BraTS 2020	Multi-task analysis	High computational cost	[30]
31	V. Sorin et al., 2023	Review on Adversarial attacks	MRI	Highlights DL vulnerabilities	No solution proposed	[31]
32	N. Dietrich et al., 2025	AI Security in Radiology	MRI	Discusses cyber threats	No hybrid solution	[32]
33	G. W. Muoka et al., 2023	Review	Medical imaging	Summarizes attack & defense strategies	Not experimental	[33]
34	M. Z. Joel et al., 2022	Adversarial robustness	MRI	Tests DL models with adversarial images	Limited datasets	[34]
35	S. Al Hasan et al., 2025	DSIT-UNet	BraTS 2020	Dual-stream iterative Transformer	Heavy architecture	[35]
36	M. Zhou et al., 2024	VQ-GAN + Transformer	BraTS 2020	3D tumor region generation	Computationally complex	[36]
37	M. Zhang et al., 2025	Generative DacFormer	BraTS 2020	GAN-based segmentation	Limited interpretability	[37]

38	L. Huang et al., 2022	Transformer GAN	BraTS 2020	Improved segmentation using GAN	Only visual XAI	[38]
39	E. P. Onakpojeruo et al., 2024	Pix2Pix GAN	BraTS 2020	MRI tumor classification	Not hybrid CNN+Transformer	[39]
40	M. M. Yurtsever et al., 2024	StyleGANv2-ADA	BraTS 2020	Data augmentation + classification	Limited multi-modal	[40]

1.7 Research Methodology

The goal of the proposed research is to create a hybrid deep learning system that is easy to use for those who know Python and can find brain tumors in MRI scans. The study will use an algorithmic method that is not yet clear. The idea is to develop a framework that combines CNNs (sometimes called Convolutional Neural Networks) with a clear and useful way to pay attention. This method is easy to use and understand, which makes it perfect for real-world multi-modal MRI research.

The project will mostly utilize pre-existing data, including BraTS 2020–2023. We will utilize your data to learn and test. During processing, MRI intensities are standardized, non-brain tissues are removed from the skull, pictures are reduced and resampled to suit standard sizes, and data is made more stable and generalizable by flipping, rotating, and scaling. We will examine each MRI type (T1, T2, FLAIR, and T1c) individually and subsequently integrate them through either straightforward combination or channel stacking to enhance our understanding of the tumor by utilizing additional information that aids in its comprehension.

The most significant part of the algorithm will be the CNN layers that hunt for local features. After that, a simple attention system will look at the tumors and learn about the region around them. You can use either a simple parser or fully connected layers to group tumors and make masks for segmentation. We will utilize heatmaps to show which parts of the model are most

important for making predictions. This will help you understand the facts better. The processed dataset will train the model, a distinct validation set will test it, and finally it will be utilized to make segmentation masks. They will use standard methods like IoU, Dice score, accuracy, sensitivity, and specificity to figure out what kind of tumor it is and give it a grade. It will also be examined to evaluate how well it works in hospitals when time and money are tight. It will be made with Python, TensorFlow, PyTorch, NumPy, OpenCV, and scikit-learn, among other things. This part will show the outcomes. Google Colab and other systems that use GPUs can help speed up the training process. The goal of this strategy is to be brief, basic, and useful in real life. Because of this, the study might focus on finding a rapid, easy-to-use, and reliable technique to discover brain cancer using academic research with real-world uses.

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